Titanic Dataset - Data Cleaning & Exploratory Data Analysis (EDA)

Performing data cleaning and exploratory data analysis on the Titanic dataset.

```
In [3]: # Import Libraries
  import pandas as pd
  import numpy as np
  import matplotlib.pyplot as plt
  import seaborn as sns

%matplotlib inline
  sns.set_style('whitegrid')
```

In [5]: df = pd.read_csv('C:\\Users\\Shouvik\\Downloads\\titanic\\train.csv')
 df.head()

5]:		PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
	0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
	1	2	. 1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.2833
	2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
	3	4	. 1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
	4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500
	4										•
	df	.tail()									

Out[7]:		PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
	886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00
	887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00
	888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45
	889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00
	890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75
	4 (•

Dataset Overview

Let's explore the structure and summary of the Titanic dataset.

```
In [8]: # Basic info about the dataset
df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype				
0	PassengerId	891 non-null	int64				
1	Survived	891 non-null	int64				
2	Pclass	891 non-null	int64				
3	Name	891 non-null	object				
4	Sex	891 non-null	object				
5	Age	714 non-null	float64				
6	SibSp	891 non-null	int64				
7	Parch	891 non-null	int64				
8	Ticket	891 non-null	object				
9	Fare	891 non-null	float64				
10	Cabin	204 non-null	object				
11	Embarked	889 non-null	object				
<pre>dtypes: float64(2), int64(5), object(5)</pre>							

memory usage: 83.7+ KB

```
# Shape of the dataset (rows, columns)
 In [9]:
          print("\nShape:", df.shape)
        Shape: (891, 12)
In [10]: # Summary statistics
          df.describe()
Out[10]:
                  PassengerId
                                 Survived
                                                Pclass
                                                                         SibSp
                                                                                     Parch
                                                              Age
                                                                                                  Far€
          count
                   891.000000
                               891.000000 891.000000
                                                       714.000000
                                                                   891.000000
                                                                                891.000000
                                                                                            891.000000
                   446.000000
                                 0.383838
                                             2.308642
                                                        29.699118
                                                                      0.523008
                                                                                  0.381594
                                                                                             32.204208
           mean
             std
                   257.353842
                                 0.486592
                                             0.836071
                                                         14.526497
                                                                      1.102743
                                                                                  0.806057
                                                                                             49.693429
            min
                     1.000000
                                 0.000000
                                              1.000000
                                                          0.420000
                                                                      0.000000
                                                                                  0.000000
                                                                                              0.000000
            25%
                   223.500000
                                 0.000000
                                             2.000000
                                                        20.125000
                                                                      0.000000
                                                                                  0.000000
                                                                                              7.910400
            50%
                   446.000000
                                 0.000000
                                             3.000000
                                                        28.000000
                                                                      0.000000
                                                                                  0.000000
                                                                                             14.454200
            75%
                   668.500000
                                 1.000000
                                             3.000000
                                                         38.000000
                                                                      1.000000
                                                                                  0.000000
                                                                                             31.000000
            max
                   891.000000
                                 1.000000
                                              3.000000
                                                        80.000000
                                                                      8.000000
                                                                                  6.000000 512.329200
         # Missing values in each column
In [11]:
          df.isnull().sum()
Out[11]: PassengerId
                             0
          Survived
                             0
          Pclass
                             0
          Name
                             0
          Sex
                             0
                           177
          Age
          SibSp
                             0
          Parch
                             0
          Ticket
                             0
          Fare
                             0
                           687
          Cabin
          Embarked
                             2
          dtype: int64
```

Data Cleaning

We will handle missing values in Age , Embarked , and drop the Cabin column (too many (close to 75%) missing entries).

```
In [15]: # Fill missing 'Age' with median
df.fillna({'Age': df['Age'].median()}, inplace=True)
```

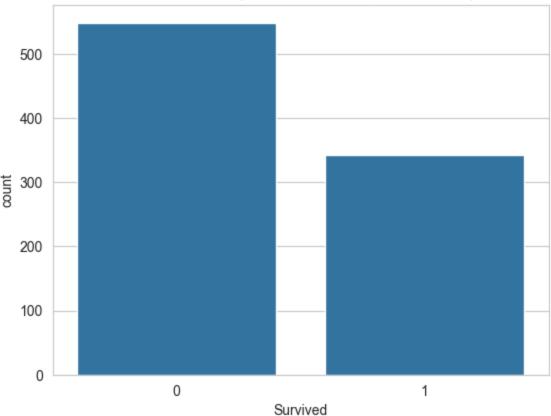
```
In [17]: # Fill missing 'Embarked' with mode
         df.fillna(df['Embarked'].mode()[0], inplace=True)
In [18]: # Drop 'Cabin' column
         df.drop('Cabin', axis=1, inplace=True)
In [19]: # Confirm missing values are handled
         df.isnull().sum()
Out[19]: PassengerId
         Survived
                        0
         Pclass
                        0
         Name
         Sex
         Age
         SibSp
         Parch
                        0
         Ticket
                        0
         Fare
         Embarked
         dtype: int64
```

Exploratory Data Analysis (EDA)

Let's explore relationships and trends in the Titanic dataset.

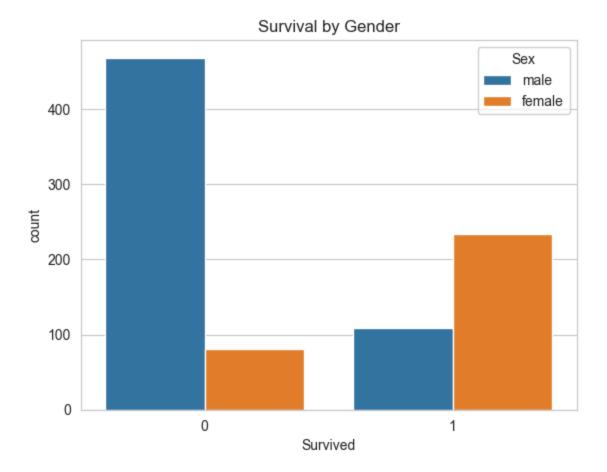
```
In [20]: # Survival count
sns.countplot(x='Survived', data=df)
plt.title('Survival Count (0 = Not Survived, 1 = Survived)')
plt.show()
```





Survival by Gender

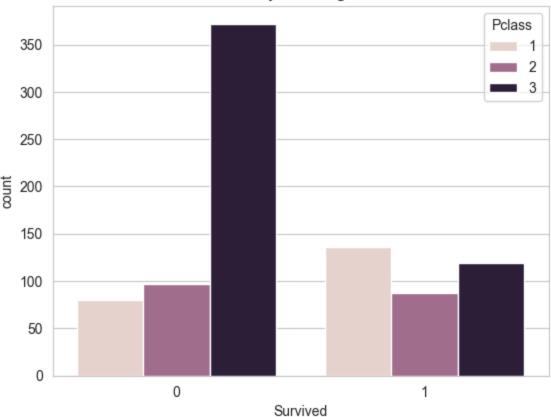
```
In [21]: sns.countplot(x='Survived', hue='Sex', data=df)
   plt.title('Survival by Gender')
   plt.show()
```



Survival by Passenger Class

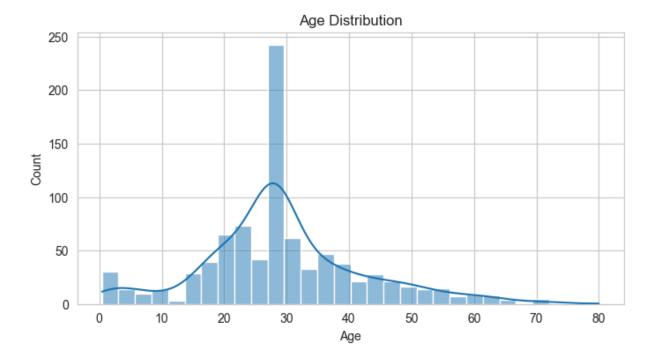
```
In [22]: sns.countplot(x='Survived', hue='Pclass', data=df)
  plt.title('Survival by Passenger Class')
  plt.show()
```





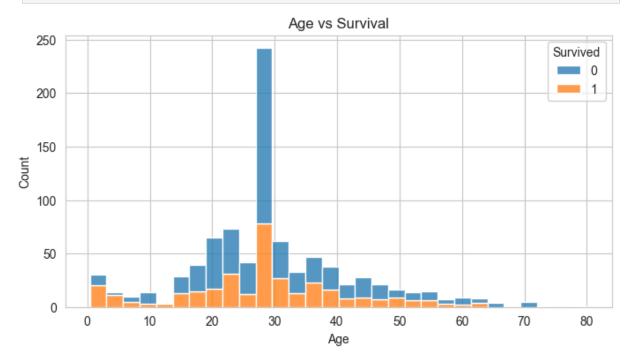
Age Distribution

```
In [23]: plt.figure(figsize=(8,4))
    sns.histplot(df['Age'], kde=True)
    plt.title('Age Distribution')
    plt.show()
```



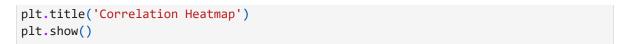
Age vs Survival

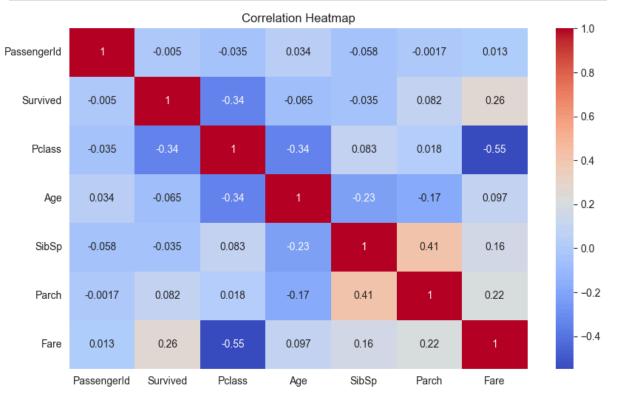
```
In [24]: plt.figure(figsize=(8,4))
    sns.histplot(data=df, x='Age', hue='Survived', multiple='stack')
    plt.title('Age vs Survival')
    plt.show()
```



Correlation Heatmap

```
In [28]: plt.figure(figsize=(10,6))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm')
```





Observations & Insights

Based on the exploratory data analysis, here are the key insights from the Titanic dataset:

- **Gender:** Female passengers had a much higher survival rate than males. Women and children were prioritized during evacuation.
- **Passenger Class:** First-class passengers had significantly higher survival chances compared to second and third class.
- **Age:** There was a tendency for younger passengers to survive more, though it wasn't a strict rule.
- **Port of Embarkation (Embarked):** Passengers from Cherbourg (C) had slightly better survival outcomes than those from other ports.
- Family (SibSp & Parch): People with small families had slightly better survival, while those alone or with large families had lower survival.

These insights help understand the human and social dynamics behind the survival patterns during the Titanic disaster.

Final Note

This cleaned and analyzed dataset is now ready for further use — such as training a machine learning model for survival prediction.

In [27]: # Save the cleaned data for further use
 df.to_csv('titanic_cleaned.csv', index=False)